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A general framework for customized transition to smart homes

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Abstract

Smart homes have the potential to achieve efficient energy consumption: households can profit from appropriately scheduled consumption. By 2020, 35% of all households in North America and 20% in Europe are expected to become smart homes. Developing a smart home requires considerable investment, and the householders expect a positive return. In this context, this work addresses the following question: what and/or when equipment should be bought for a specific site to gain a positive return on the investment? This work proposes a framework to guide the smart-home transition considering customized electricity usage. The framework is based on linear models and gives a simple payback analysis of each combination of equipment acquisition for any specific user taking into account geographical location and local conditions. It is also possible to use the framework for equipment sizing. The results quantify the dependence of the simple payback on the site and the application.

Keywords: Smart Home, Energy Management System, Simple Payback, Return on Investment, Optimization.

1. Introduction

With the growth of smart grids worldwide [1, 2] and the increased use of demand-response pricing mechanisms in the residential sector, the number of smart homes is expected to increase significantly. Governments support this trend for two reasons. First, distributed generation by smart homes allows investment in the grid infrastructure to be postponed. Second, the environmental impact is reduced if local renewable generation is used. Smart home owners may be interested in making a profit (or at least reducing their electricity bill) or maintaining a certain level of comfort via the scheduling of appliances [3].

The adoption of key devices for a transition to smart homes is highly dependent on cost concerns [4]. Household holders need to know, at least, the simple payback period of the investment in smart-home transition. A possibility for the investment is the acquisition of smart-home components (SHCs), which is defined to be the appliances, machines, and technologies available for smart homes, such as photovoltaic panels (PVs), wind turbines (WTs), combined heating and power (CHP), energy storage systems (ESSs), water heaters (WHs), electric vehicles (EVs), heating, ventilation, and air-conditioning (HVAC), and solar collectors (SCs). As mentioned in [5], “... the consideration of either

net present values or discounted payback periods are the most useful approaches as these consider the future value of money”. In this paper, the simple payback period is used instead of net present values (NPV) or discounted payback periods (DPP), since there is no real data available for maintenance costs of all specific SHCs for a specific user considered in this paper. The framework provides the householder with the annual savings. If the householder has an estimation for maintenance cost, she/he can compute, for example, the annual cash net flow and then the NPV. Thus, the last step of the proposed framework has the flexibility to incorporate other economic measures. Throughout this work, the term “payback” designates simple payback.

A challenge for householders that wish to transform their homes into smart homes is the lack of practical tools to carry out an economic analysis to select the best combination of SHCs to acquire. If householder h living at a specific location (latitude and longitude) is able to buy any of the SHCs in the set $\{SHC_1, SHC_2, \dots, SHC_{10}\}$, then the householder has 1024 combinations of SHCs to choose from. This naturally brings up the question of *which is the most profitable set of SHCs for householder h* ? This work is motivated by the need to answer this question. The main contributions of this work are a general framework that gives a payback analysis of each SHC combination for a specific user, taking into account geographical location and local conditions, and an investigation into whether there is a synergistic effect between the payback period and the return on investment.

The remainder of this paper is organized as follows. Section 2 presents related work, and Section 3 presents the

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proposed framework. Section 4 discusses the mathematical model, which is based on [3], and gives computational results. Section 5 provides concluding remarks.

2. Related Work

To the best of our knowledge, a general framework that provides a payback analysis of each possible SHC acquisition combination for a specific user taking into account geographical location and local conditions is not yet available. In Section 2.1, the literature related to the topic is summarized, and in Section 2.2, the contributions of this work are explained.

2.1. Literature Summary

Xu et al. [6] propose a scheduling model that finds the best combination and the optimal capacities of batteries, water tanks, and ice/heat storage units under time-of-use electricity prices. They consider PV, SC, WH, CHP, and HVAC as well as these storage devices. Their mixed-integer linear programming (MILP) problem minimizes the total cost of electricity, natural gas, and the investment cost of the storage devices. For each of the three cities considered, the authors compare a solution from a deterministic scenario with solutions that consider the solar radiation and demand profiles to be uncertain. Their tree method considers the expected cost in all scenarios jointly. The costs are minimized and projected over a one-year horizon. The results show that thermal storage units and water tanks are profitable, but batteries have short lifetimes and high investment costs.

Van der Stelt et al. [7] present a techno-economic analysis of household batteries and community energy storage, i.e., an ESS shared by several houses, for residential prosumers with smart appliances. Using real demand and PV generation data from 39 households in the Netherlands, the authors calculate the levelized costs of energy and the payback period for the ESS systems. Shiftable appliances are also considered. They formulate an MILP problem that minimizes the cost of energy acquisition from the grid. They assume that the user can inject electricity into the grid but without remuneration. The horizon is one year. They find that the savings are too small to recover the investment costs within the lifetime of the systems: the payback period ranges from 26 to 43 years.

Akinyele & Rayudu [8] present a comprehensive review of energy storage technologies with their technological development status and capital costs. They show a high cost (500–2500 \$/kWh) for lithium-ion batteries.

Monyei et al. [9] propose a biased load manager home energy management system for low-cost residential buildings using the Matlab simulation environment. A case study in Naira (Nigeria) shows that the payback period is between 8.4 and 25 years.

Barbieri et al. [10] study the profitability of μ -CHP systems for residential buildings. They show that the Stirling engine has the best performance, with a payback period of 7 and 14 years if prices are respectively 3000 and 6000 €/kW. They build a simulation model in Excel in which there is a scheduling optimization problem for a μ -CHP component that is solved by a genetic algorithm.

Asaee et al. [11] investigate, in a Canadian context, the energy system, greenhouse gas (GHG) emissions, and economic performance of a co-generation system based on an internal combustion engine (ICE). The analysis is based on the whole building through simulation with the ESP-r software. As the capital cost estimation was not available, the measure used was the tolerable capital cost. The results showed that the ICE is cost-effective.

Barbieri et al. [12] conclude, in 2012 for the UK, that the absence of subsidies and, in particular, a reduction in taxes on natural gas did not make certain μ -CHP technologies attractive. Later, Conroy et al. [13] studied a Stirling engine in the UK, comparing the economic performance and the GHG of the μ -CHP against a condensing gas boiler. They found that the payback period is 13.8 years higher than that for the boiler. Their study was based on field trial data for June 2004 to July 2005.

In the UK context, Merkel et al. [14] propose a scheduling MILP formulation to minimize the total annual cost. While the μ -CHP is more detailed, the thermal storage is represented by a temporal balancing equation and the boiler has power-limit constraints. They use three weeks per season with a scaling factor to represent a year. They find that the payback for a system with boilers and μ -CHP is not economical in three of the five buildings. For the other two buildings, the payback periods are 18.6 and 19.2 years. With thermal storage and μ -CHP, the system is profitable for all five buildings, with a payback period between 13.1 and 17.3 years.

Six et al. [15] study market opportunities for μ -CHP in Flanders using simulation with TRNSYS. The results show that the payback period is longer than the life-span of the project.

Dufo-López et al. [16] present an hourly management method for energy generated in grid-connected wind farms using battery storage (wind–battery systems) and hydrogen (wind–hydrogen system); these are analyzed technically and economically. They calculate the investment cost and discounted present values for large systems (2.5 MW for WT and 2 MWh for batteries). They perform a simulation over one year with the GRHYSO software to represent the system life-span of 20 years. They find that when the electricity selling price is higher than the market average, a system composed of batteries and WTs is more cost-effective than wind-only systems.

Akter et al. [5] present an Australian case: they propose a framework that assesses a battery system with PVs. The results show that the payback period and net present value (NPV) of this system are worse than those for systems with PVs only. PVs are found to be profitable in

on-grid systems but unprofitable in off-grid systems because of the waste of energy, after a threshold of installed capacity. The authors consider different tariffs and reductions in CO₂ emissions, using simulation to explore the scenarios for a project with a life-span of 25 years.

Cherrington et al. [17] perform a financial analysis of two installations in Cornwall (UK) to determine the impact of different feed-in tariffs (FITs) in a PV system with a capacity around 2kW. The capital cost is £11000. Given annual inflation of 8%, a grid injection limit from PV generation of 50%, an annual efficiency loss, and an annual reduction in the total installation cost, the authors find payback periods in the range of 9–12 years and net profit in the range of £14400–32543. However, a similar study [18] that considers a PV system of 3kW with the same capital cost and annual inflation of 6% shows that PV without FIT is not profitable in 17 of 20 British cities. With FIT and a grid injection limit from PV generation of 50%, in all 20 cities the PV capital cost is decreased by £1000–7000. The authors perform a simulation using the PVSyst software in which the PV generation profiles are estimated by the average of twelve PV hourly outputs.

Aagreh et al. [19] present a feasibility analysis for a small hotel of combinations of PV, WT, an off-grid system with a battery, and an on-grid system. They perform a simulation with the HOMER software for a 25-year horizon. In the on-grid case, when the price for selling electricity back to the grid is null, the payback period for the PV system exceeds the lifespan. When the selling price is half of the market price, PVs become profitable for small capacities. WT systems without batteries and PVs are profitable (see Tables 2 and 3 of [19]) for the cases considered. The payback periods for a system with batteries are not given.

Mamouri & Bénard [20] present an evaluation of solar water heaters in 26 dispersed locations in Michigan for an average life-span of 20 years. They use the System Advisor Model simulation software and find a payback period between 8.1 and 9.3 years.

Xie et al. [21] study a detailed house design using the SketchUp modeling software. They analyze the payback for PVs, SC, a hybrid of PV and thermal panels (PVT), heat pumps, phase-changing materials, and μ -CHP systems. The results show payback periods of at least 6.5, 13, and 11 years for WH, μ -CHP, and PVs/PVT, respectively.

To the best of our knowledge, there are no studies of EV payback in the context of smart homes. However, a comprehensive ownership cost model to calculate the costs of purchase and use has been developed [22].

The work in [23] proposes a techno-economic analysis for home automation, which is defined to be a home with the integration of technologies that is controlled manually by a single component (HEMS) but without optimization strategies. Three scenarios are considered in a northern Italian house. The first scenario considers the transition from current home to a home automation system concept

with a focus on lighting. The second scenario considers, beyond the home automation concept, the replacement of old appliances by smart appliances that are more efficient in terms of consumption. The third scenario considers the two previous ones plus PV. A yearly consumption estimation is considered for each electrical device, so consumption savings are directly reported for each device. Considering a required rate of return of 4%, the authors conclude that the first scenario has the highest economic viability followed by the second scenario with a positive return. However, the third scenario has a negative payback. A main difference between this work and that in [23] is that this work uses optimization for every possible scenario.

Meena *et al* [24] study the profitability of a system composed of WT, PV, and battery in an Indian context. For a fixed power demand, the size of these components is optimized to maximize the NPV. A heuristic is used for the resolution. Although the authors consider maintenance costs, the replacement cost of batteries once warranty ends is not taken into account. The results show that the best sizing is 2kW for WT, 4.2kW for PV and 11.2kWh of battery capacity, with a payback period of 5 years and an NPV of USD\$20 for a required rate of return of 5%. A main difference between this work and that in [24] is that this work uses exact methods and detailed appliance models for power demand, and it explores the use of many SHC.

2.2. Contributions

The literature has focused on payback for isolated or a few combinations of SHCs. The results suggest that each system will have its own payback. However, current research does not explore every SHC acquisition possibility for a specific user independently of geographical location. As mentioned in [8], the benchmarking costs of ESS depend on the application and on the site. This work assumes that every system depends on the application, in our case, a specific consumption pattern, that changes for each user. The goal is a tool to assist householders in their decisions about the transition to a smart home.

From Section 2.1, one can note that the majority of the literature uses simulation methods to analyze the profitability of some combinations of SHCs. In a simulation, one creates a behavioral model of the smart home in order to simulate it. Behavioral modes need decision rules at each time step that must be explicitly configured by the user. Based on the decision rules, the behavioral model computes the state of each SHC at each time step knowing the events that occur between consecutive time steps. An example of a decision rule is the following: *For the set {ESS, HVAC, WT}, if an amount of energy is available at a time step with high prices, divide it as follows: send $x\%$ to ESS, $y\%$ to HVAC and $z\%$ to WH.* Note that x , y and z are decided in advance by the user. In practice, setting it up is time consuming because there are many combinations to be configured, and for each combination

there are many time steps. In addition, the optimality of the solution cannot be guaranteed.

Optimization methods overcome these issues, but they can oversimplify the problem during the modeling stage. Within the literature that uses optimization methods to analyze the profitability of some sets of SHC, only Xu et al. [6] have explored multiple combinations for the following set of SHCs: ESS, WH, ice/heat storage. However, many other sets are possible, not only considering different appliances, but also different sizes for them. The main contribution of this work is to explore every SHC acquisition combination for a specific user taking into account geographical location and local conditions. Moreover, representative appliance models are used and their integration is considered. The result is a tool that determines the best investment in the transition from an existing home to a smart home.

3. Framework

The proposed framework is illustrated in Figure 1: the ellipses represent optimization problems and the rectangles represent results.

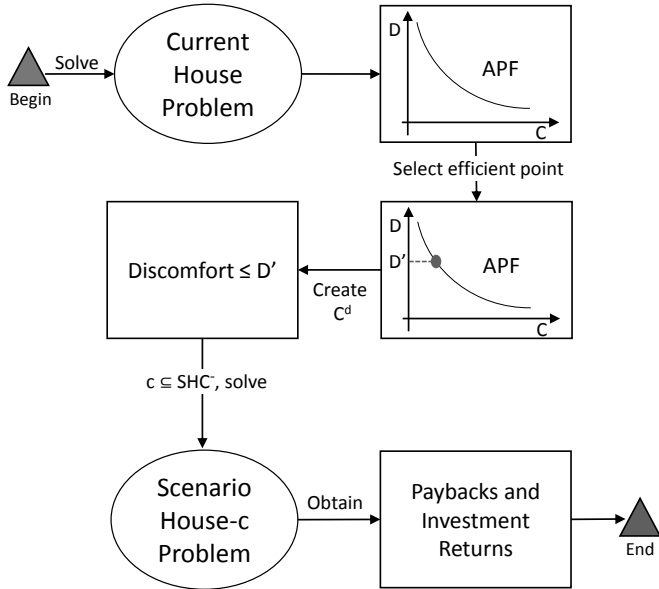


Figure 1: Proposed framework.

Let SHC^- be the set of SHC that are not already available at the house. The goal is to calculate the payback period and the return on investment of every combination in SHC^- . The first step is to determine the compromise between cost and comfort level. These are conflicting objectives, and there are multiple Pareto-optimal solutions. Hence, multi-objective optimization (MOO) [25] can be applied to obtain an approximate Pareto front (APF) of this trade-off.

A detailed MILP model was presented in [3] to find an optimal trade-off between cost and comfort by minimizing a weighted sum of the two objectives. This work adapts

it to the APF approach. Let T be the set of time steps. The model schedules the energy consumption for one day divided into $|T| = 144$ time intervals with fixed length of 10 minutes. The appliances are grouped as follows:

- A : Set of electrical appliances;
- $A_I \subseteq A$: Set of appliances with uninterruptible operation;
- A_I^* : Set of tasks for appliances in A_I .
- $A_P \subseteq A$: Set of appliances with interruptible phases;
- A_P^* : Set of tasks for appliances in A_P ;
- $A^* = \{A_P^* \cup A_I^*\}$: Set of tasks for appliances in A .

Let \mathcal{X} be the space of all variables and $\Xi \in \mathcal{X}$ a solution. The full set of constraints in \mathcal{X} is available in [3], which are omitted here. The functions f_c , f_t , f_u , and f_d represent, respectively, the total cost, the thermal discomfort, the usage-time discomfort, and the total discomfort:

$$f_c(\Xi) = \sum_{t \in T} \left(C_b^t - C_s^t + C_{CHP}^t \right) + C_{ev},$$

$$f_t(\Xi) = \sum_{t \in T} \sum_{a \in A} V_a^t,$$

$$f_u(\Xi) = r_1 \left[\sum_{k \in A_P^*} \sum_{p=1}^{P_k} \Psi_{k,p} + \sum_{k \in A_I^*} \zeta_k \right] + r_2 \sum_{t \in T} \sum_{k \in A^*} U_k^t$$

where variables: C_b^t [\$] and C_s^t [\$] represent the cost at $t \in T$ of buying and selling energy, respectively, C_{CHP}^t [\$] is the combined heating power (CHP) operation cost at $t \in T$, C_{ev} [\$] is the fuel cost for a hybrid vehicle, V_a^t [$^{\circ}\text{C}$] is the discomfort related to the deviation from the target temperature of appliance a at $t \in T$, U_k^t [hour] is the discomfort related to the deviation from the target time for task k at $t \in T$, ζ_k [hour] is the discomfort related to the omission of task $k \in A_I^*$ and $\Psi_{k,p}$ [hour] is the discomfort related to the omission of phase p of task $k \in A_P^*$. For parameters, let define P_k as the number of phases of task $k \in A_P^*$, $r_1 \in \mathcal{R}$ as the discomfort factor per task not performed and $r_2 \in \mathcal{R}$ as the discomfort factor per usage-time deviation.

Let define the “Current House Problem” to be

$$\min_{\Xi} [f_c(\Xi), f_d(\Xi) = \alpha_t f_t(\Xi) + \alpha_u f_u(\Xi)] \quad (1)$$

$$\Xi \in \mathcal{X}^{BASE} \quad (2)$$

where α_t [discomfort/ $^{\circ}\text{C}$] and α_u [discomfort/hour] are discomfort factors. \mathcal{X}^{BASE} represents the same space of \mathcal{X} , but every variable of an appliance $a \in SHC^-$ is set to zero in \mathcal{X}^{BASE} . The first step uses the above model to compute an APF, which is shown in the first rectangle in Figure 1. The next step is to select an efficient point on the APF. Suppose the decision-maker has selected a

point with discomfort level D' : see the red point in the second rectangle in Figure 1. Then, D' is used in the constraint $C^d : f_d(\Xi) \leq D'$. This is represented by the third rectangle.

For each subset $c \subseteq SHC^-$, the framework solves the optimization problem SHP^c with the constraint C^d and the constraint(s) for the components in c . The flow conservation constraint is modified to consider the components from the current house in addition to the components of c . Suppose $SHC^- = \{PV, WH, EV\}$ and $c = \{EV, WH\}$. Then SHP^c is the MILP problem

$$\min_{\Xi} f_c(\Xi) \quad (3)$$

$$f_d(\Xi) \leq D' \quad (4)$$

$$\Xi \in \mathcal{X}^{EV} \quad (5)$$

$$\Xi \in \mathcal{X}^{WH} \quad (6)$$

$$\Xi \in \mathcal{X}^{BASE} \quad (7)$$

Objective function (3) minimizes the consumer cost. Constraint (4) ensures a maximum discomfort level D' . In Constraints (5) and (6), \mathcal{X}^{EV} and \mathcal{X}^{WH} means a set of feasible points for EV and WH constraints, respectively. Constraints (5) and (6) control the operation of the EV and WH, respectively. Finally, (7) are the constraints from (2) with the flow conservation constraint adjusted to consider the EV and WH.

The payback is computed in the last framework step, which is represented by the last rectangle in Figure 1. Let D^p be the project duration, Pay^B the payback period, s^{slp} the savings over the life-span, T^I the total investment, and I^R the return on investment. The payback is calculated [5, Section 3.4] as $Pay^B = D^p T^I / s^{slp}$ and $I^R = s^{slp} - T^I$. If Pay^B is greater than the life-span then the project is not cost-effective.

4. Results and Discussion

In this section, the framework is applied to three case studies. This work considers an horizon of 25 years, and the exchange rates used are 1 USD = 0.71 GBP, 1 USD = 1.27 CAD, and 1 USD = 3.3 BRL. The houses have appliances with distinct daily tasks A^t , a fridge, a shower, and an HVAC system. The houses considered are located in Belo Horizonte (BH), Brazil; London, U.K.; and Montreal, Canada. The MILP problems were solved using Gurobi 8.0.0.

For BH and London, this work does not consider inflation; it assumes that the customer wishes to acquire a system now. A total of 1024 systems are evaluated based on an annual savings approach: 365 days are optimized and the sum of the daily savings gives the annual savings. The total saving for a specific project is the product of the annual saving and the duration.

For Montreal, this work considers inflation: the cost of the SHCs and electricity prices change over time. A total of 64 systems are evaluated. The optimization is applied

daily from 2019 to 2080, covering projects starting between 2019 and 2055, since each has a duration of 25 years. If a project starts in January 2020, sum of savings of the next 365×25 days is done to obtain the total savings. At the end, the output is: which and when the SHCs for a specific user in Montreal should be acquired such that it will be profitable.

For the appliances $a \in A_{IEUI} \cup A_{Phases}$, a dataset with real daily load profiles is available [26]. A set of load profiles is created for each day of the week. In the optimization, for each day of the week, a load profile is randomly selected from the corresponding set. Thermal mass of building, solar radiation, wind speed, etc., are considered in constraints proposed in [3], which are also used in this work. For more details, hypotheses and justifications for all decisions related to the SHC models and pricing policies are defined in [3]. In addition, $\alpha_u = \alpha_t = 1$.

4.1. BH Case

The BH house does not have PV, Battery, WT, SC, WH, EV, or μ -CHP. Let use $SHC^- = \{PV \text{ 3.5kW, PV 6.5kW, Battery 26kWh, Battery 13kWh, WT 3kW, WT 7kW, SC, WH, EV, } \mu\text{-CHP}\}$. When similar components are in the same subset $c \subseteq SHC^-$, they are replaced by a new component with a capacity equal to the sum of the capacities of these components. The house does not have the infrastructure for natural gas, so the ICE is set to μ -CHP. Table 1 summarizes the set SHC^- . The first column lists the element and the second column gives its brand and model. In the second column, some SHCs have the number of units that must be acquired to achieve the desired capacity, for instance, the PV 3.5kW need 14 units of CS CS5P-250M to achieve a capacity of 3.5kW. The third column gives the warranty, which is considered to be the life-span, and the fourth and fifth columns give the prices, in USD and BRL respectively. The sixth column gives the total price including installation cost and additional materials. Unless otherwise stated, no maintenance costs is considered: when the warranty ends, the SHC is replaced. The total daily distance (in km) for EVs is drawn from the uniform distribution $U[0,70]$. The PV simulation model considers many parameters such as sun position, PV orientation, ground reflectance, latitude, longitude and solar radiation. For the solar radiation, the percentage of clouds are used for each month from [27], which is shown in Figure 2. This avoids overestimating the solar radiation by assuming clear skies. The other parameters are set as in [3].

4.1.1. APF Results

The ϵ -constraint [36, Algorithm 1] is used to obtain an APF, which is shown in Figure 3. The efficient solutions found in Figure 3 could be presented to the DM, but to aid the selection process MDIPNW [37] was used to select an efficient point such as the one with coordinate (C', D') . With this coordinate, the framework creates a constraint

Table 1: SHC summary for BH case

SHC	Brand and Model	Life-span (years)	Price (USD)	Price (R\$)	Total Cost (R\$)
PV 3.5 kW	14 × CS CS5P-250M	25 ^a	14 × 225 [28]	11781 ^b	17671.50
Battery 26 kWh	2 × Tesla Powerwall	10 [29]	12500 [29]	41250 ^b	61875
WT 3 kW	3 × Bergey Excel 1 kW	5 ^a	3 × 4995 ^c	49450.5 ^b	74175.75
SC	Coupled Tempersol [30]	5 ^a		1400 [30]	2100
WH	Rheem 80G	10 [31]	1899 [31]	6266.7 ^b	9400.05
EV	2018 Nissan Leaf	5 ^a	30000 [32]	120000 [33]	43500
μ -CHP	Yanmar CP5WN-SNB	2 ^a		3950 [34]	5925
PV 6.5 kW	26 × CS CS5P-250M	25 ^a	26 × 225 [28]	21879 ^b	32818.5
Battery 13 kWh	1 Tesla Powerwall	10 [29]	6600 [29]	21780 ^b	32670
WT 7 kW	Bergey Excel 1 kW + Bergey Excel 6 kW	5 ^a	10000 ^c	330000 ^b	49500
WT 10 kW	Bergey Excel 10 kW	10 [35]	31770 ^c	104841 ^b	104841

a: According to the manufacturers's datasheet

c: Given by the manufacturer

b: Value converted from USD to BRL

CS: Canadian Solar

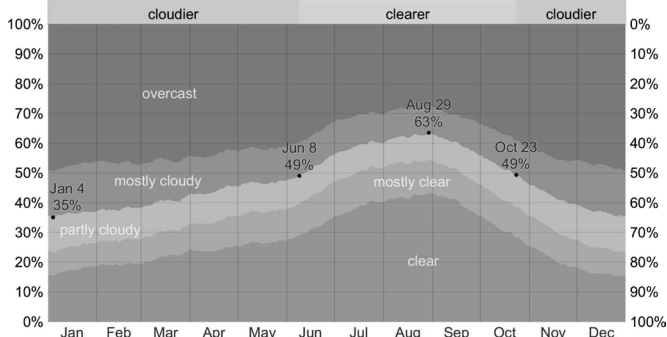
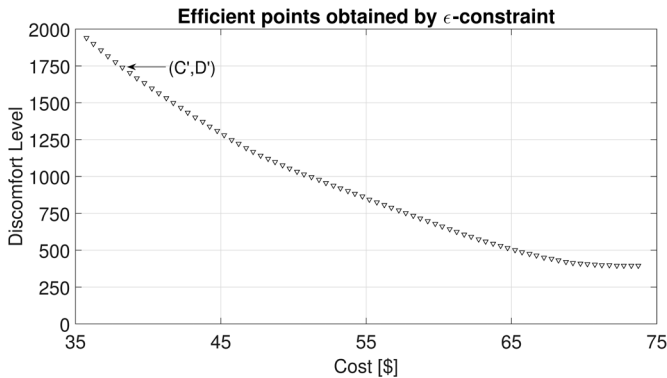


Figure 2: Percentage of time spent in each cloud cover band at BH, categorized by the percentage of the sky covered by clouds: clear < 20%; mostly clear < 40%; partly cloudy < 60%; mostly cloudy < 80%; overcast > 80%. Source: [27].

C^d to control the maximum level of discomfort. It is worth mentioning that MDIPNW is not an exclusive method to help in selecting efficient points. Other methods exist and can be applied; see e.g. [38].

Figure 3: APF and point selected to construct C^d .

4.1.2. Solving SHP^c

For each subset $c \subseteq SHC^-$ defined in Section 4.1, the problem SHP^c is solved. The number of sets is $2^n - 1$ because $c = \emptyset$ represents the existing scenario, which was handled in the first step of the framework.

4.1.3. Payback and Investment Return

Since some SHCs have life-spans below 25 years, the total cost was increased in proportion. For instance, the 3 kW WT has a life-span of five years, so five units are needed to cover 25 years.

For each SHP^c, the total investment is found by summing the total cost of each component of c , as well as the payback and the return on investment: see the formulas given in Section 3.

4.1.4. BH Results

Table 2: BH results

Component	Payback (years)	Return on investment (thousand R\$)
PVs, 3.5 kW	7.57	40.632
PVs, 6.5 kW	8.59	62.656
PVs, 10 kW	9.13	87.784
WTs, 7 kW	19.58	68.489
WTs, 10 kW	22.60	41.809
SC	11.41	12.513

Table 2 summarizes some cost-effective combinations. An interesting finding is the relationship between the renewable generators. The expected synergy does not occur: the sum of their separate investment returns (IRs) is greater than the combined IR.

In this case, batteries are too expensive. Every set c with a battery has an IR lower than that without a battery; sometimes the former value is negative. The price of a Tesla battery pack must decrease to 223.5 USD to pay for itself without renewable generation. Systems composed of a battery and renewable generation have a negative IR. In these systems, the price of a 26 kWh battery must be 1650 USD to match the IR of a 3.5 kW PV system; 100 USD to match that of an SC system; and 1500 USD to match that of a 7 kW WT system.

The price of an EV must be at most 58073 R\$ to be cost-effective. If the DM is going to buy a car costing x

R\$, the price of an EV must be at most $x + 58073$ R\$. If one considers a life-span of 10 years for EVs, the price must be at most 116140 R\$.

SC is a better option for water heating because a) WH systems, or b) WH and SC systems, or c) μ -CHP, WH, and SC systems are not cost-effective. μ -CHP is not cost-effective even if its price is halved because of its short life-span; it starts to be profitable if its life-span increases to 13 years. However, the payback could be interesting if a μ -CHP powered by natural gas were available. In an industrial context, [39] showed a payback in less than five years for a μ -CHP powered by natural gas in a city near BH.

For this customer, the set {10kW PV, SC, 7kW WT} gives the best IR (141.282 thousand R\$) with a payback in 17.14 years. The set {3.5kW PV} has the smallest positive payback.

4.2. London Case

The same SHC^- as for BH is considered. The acquisition price per kWh is that for the tariff *HomeEnergy Fix Mar 2019*, from British Gas. The time of use has two stages: £0.175 from 7:00 a.m. to 10:59 p.m. and £0.0912 otherwise [46, 47]. The selling price per kWh is set to £0.0524 following the FIT export tariff in [48]. The price of natural gas is £0.0361/kWh from the tariff *Safeguard PAYG* [47]. The fuel price is set to the average diesel price in April 2018 [49]: £1.25/L. The ground temperature was obtained from [50], and the house's heat resistance is based on [51, Table 2]. The Weibull parameter for wind speed is taken from [52, Table 8.5 - London Array I]. The nominal power of 5 kW for HVAC is considered to be at least 50% of the measuring heating capacity from [53]. The total daily distance (in km) for EVs is drawn from the uniform distribution $U[0,70]$. The parameters for the economic analysis are given in Table 3. It is similar to Table 1, but some elements in the column "Price (£)" include the total cost of equipment and installation. Other costs are added in the column "Total Cost (£)." Unless otherwise stated, no maintenance costs is considered: when the warranty ends, the SHC is replaced. For the solar radiation, the percentage of clouds is used for each month from [27], which is shown in Figure 4. The other parameters are set as in [3].

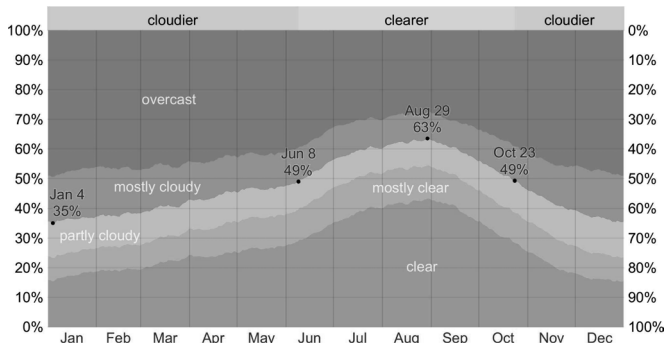


Figure 4: Percentage of time spent in each cloud cover band at London. Source: [27].

4.2.1. London Results

Table 4 summarizes some cost-effective combinations. PVs have a payback inversely proportional to the nominal power, and the best IR is for the medium size. The estimates computed by the proposed framework are worse than [17] and better than [18]. Compared with [17], the payback period found by the proposed framework is 5 to 7 years longer, and the IR is £12k to 30k lower for the 3.5kW PV. An important difference between this study and [17] is that this work does not consider annual inflation of 8%. For a payback of 12 years in this study, the total savings over 25 years increase by £1500, which happens if electricity increases by 8% annually. For [18], in London, a 3kW PV system with FIT has to cost at most £5 k to be self-sustaining. If the 3.5 kW PV costs £8.6 k, it will still have a positive IR. A difference between this work and that in [18] is that this work uses a detailed optimization method over a whole year. Thus, the PV energy will be used in an optimal way, which can reduce the payback period.

The framework can be used also to determine the best sizing for some SHCs. From Table 2, the best capacity size for PV is between 3.5kW and 10kW based on the economic measures. The framework could be executed again replacing the PV 3.5kW and PV 10kW by PV 5kW and PV 8.5kW, respectively, so that find a better approximation for the best size of the PV.

SC would not be cost-effective even if its life-span were 25 years. If its price drops to £2065, it starts to be profitable. A two-year life-span for WH makes it a costly option. It must increase its life-span to 14 years or decrease its price to £192 to become cost-effective.

Only the 10kW WT has a positive IR. For an annual mean wind speed above 7 m/s, since the 10kW WT has a cost of £5640/kW, this result is in line with [54, Table 13] that specifies a viable initial cost below £7548/kW for the generation capacity.

As for BH, batteries are too expensive. Lower battery capacities have lower losses. For the system with a 10kW WT and a 13kWh battery, the battery cost must decrease to 1000 USD to match the IR of the corresponding system without a battery. With the exception of systems with a 10kW WT, every system composed of ESS and PVs or ESS and SC has a negative IR.

Although batteries are not profitable, EV is cost-effective if the life-span is 10 years: the payback is 23.81 years with an IR of £2.731 k. Taking into account the UK plug-in grant [55] of £4500, the payback drops to 18.94 years with an IR of £13.981 k.

BlueGen is unprofitable: the payback is 83 years. It remains unprofitable if the life-span of this μ -CHP increases to 25 years. However, with a life-span of 25 years and the same costs as in [14], the payback is 17.52 years, which is in line with the results of [14]. Given the FIT tariff of £0.1454 in June 2018 for CHP [48], BlueGen is profitable (17.91 years and £22.84 k). If an ICE were used, such as

Table 3: SHC summary for London case

SHC	Brand and Model	Life-span (years)	Price (USD)	Price (£)	Total Cost (£)
PV 3.5 kW	CS CS5P-250M	25 ^a		5906.25 [40]	5906.25
Battery 26 kWh	2 × Tesla Powerwall	10 [29]	12500 [29]	8875 ^{b*}	13312.50
WT 3 kW	3 × Bergey Excel 1 kW	5 ^a		15000 [41]	15000.00
SC	Pure Energy 16	15 ^a		4500 [42]	4500.00
WH	Megafluo Eco Unvented Indirect 300L	2 ^a		1319.5* [43]	1979.25
EV	2018 Nissan Leaf	5 ^a		21990 [44]	21990.00
μ -CHP	BlueGen	10 ^a		15500* [45]	23250.00
PV 6.5 kW	CS CS5P-250M	25 ^a		10968.75 [40]	10968.75
Battery 13 kWh	1 Tesla Powerwall	10 [29]	6600 [29]	4686 ^{b*}	7029.00
WT 7 kW	Bergey Excel 1 kW + Bergey Excel 6 kW	5 ^a		36000 ^d	36000.00
WT 10 kW	Bergey Excel 10 kW	10 [35]	31770 ^c	22556.7 ^{b*}	33835.05

a: According to the manufacturers's datasheet
b: Value converted from USD to GBP
c: Given by the manufacturer
CS: Canadian Solar
d: Sum of 1 WT 1 kW and 1 WT 6 kW from [41]
*: Does not include installation cost

Table 4: London results

Component	Payback (years)	Return on investment (thousand R\$)
PVs, 3.5 kW	17.30	2.789
PVs, 6.5 kW	18.72	3.619
PVs, 10 kW	22.01	2.241
WTs, 10 kW	9.09	98.676

the one in Table 1, the μ -CHP would never be profitable.

The best payback is for {10 kW WT}. With the plug-in grant and an EV lifespan of 10 years, the best set becomes {10 kW WT, EV} (11.34 years and £120.558 k).

4.3. Montreal Case

In Montreal, it is generally believed that PV is not profitable because of the low price of electricity. The appliances that are not currently available are PV, EV, battery, and SC. Thus, the set SHC^- is composed of PV 3.5 kW, Battery 26 kWh, SC, EV, PV 6.5 kW, and Battery 13 kWh. Although Montreal is cold for almost half of the year, SC is used [56]. CHP is discouraged by governmental programs for GHG reductions; even natural gas is considered undesirable [57].

The acquisition price per kWh is given in [58]. Beyond a fixed price for electricity availability, the tariff can be seen as an inclining block rate (IBR) with two blocks: \$0.0591/kWh if the consumption is below 36 kWh per day and \$0.0912/kWh otherwise. To represent this, one may consider a block with a capacity of 36 kWh and a discount of 35% that can be completely used. Note that the utility does not pay for electricity injected into the grid but gives the customer a credit in kWh that is valid for two years. It is considered to be equivalent to the utility buying electricity at the selling price, but this work assumes that the compensation can be applied after two years.

The fuel prices are set to the average diesel price in April 2018 [59]: 1.40 CAD. The nominal power for HVAC

is set to 5 kW. The ground temperature is assumed to be between 5°C and 10°C, following [60, Figure 12]. The house's heat resistance is taken from sections 34 and 37 of *Quebec's Regulation Respecting Energy Conservation in New Buildings*. The total daily distance (in km) for EVs is drawn from the uniform distribution $U[0,70]$. The other parameters are set as in [3].

According to Hydro-Québec [61], electricity prices follow the consumer price index (CPI), which varies between 0.5% and 3% annually for 1997 to 2017 [62]. Ran et al. [63, page 23] show that from 2010 to 2017 there was a 61% reduction in the residential PV system cost benchmark and from 2016 to 2017 there was a 6% reduction. This work assumes that PV prices fall by 6% per year, but, to take into account the effect of learning curves [64], the percentage is multiplied by 0.98 at the beginning of each year to give a more conservative decrease. Following [65, page 12], this work considered a decreasing cost of 10.3% per year for batteries; this is multiplied by 0.9 each year to give a more conservative decrease. The same value is used for the decreasing cost of EVs, since batteries are considered a key component in terms of overall cost and performance [66]. SC technologies are already well developed and can be bought at low prices [67], so an annually decreasing cost is not applied. The parameters for the economic analysis are given in Table 5. The installation costs, a component of the *Total Cost*, were provided by local suppliers.

4.3.1. Montreal Results

For the solar radiation, this work considered the percentage of clouds for each month [27], which is shown in Figure 5.

The annual savings for some subsets $c \subseteq SHC^-$ are shown in Figure 6. The total savings, for the duration of the project, are given in Figure 7. For example, in Figure 6, each year from 2019 to 2079 has an annual saving for each component. For instance, the 3.5 kW PV has an

Table 5: SHC summary for Montreal case

SHC	Brand and Model	Life-span (years)	Price (USD)	Price (CAD)	Total Cost (CAD)
PV 3.5 kW	14 × CS CS5P-250M	25 ^a	14 × 225 [28]	4533.9 ^b	10881.3
Battery 26 kWh	2 × Tesla Powerwall	10 [29]	12500 [29]	15875 ^b	23812.50
SC	Heliodyne GOBI 408-001	10 ^a	1070.99 [68]	1360.16 ^b	2040.24
EV	2018 Nissan Leaf	5 ^a	30000 [32]	38100 ^b	38100
PV 6.5 kW	26 × CS CS5P-250M	25 ^a	26 × 225 [28]	8420.1 ^b	20208.24
Battery 13 kWh	1 Tesla Powerwall	10 [29]	6600 [29]	8382 ^b	12573

a: According to the manufacturers's datasheet

b: Value converted from USD to CAD

CS: Canadian Solar

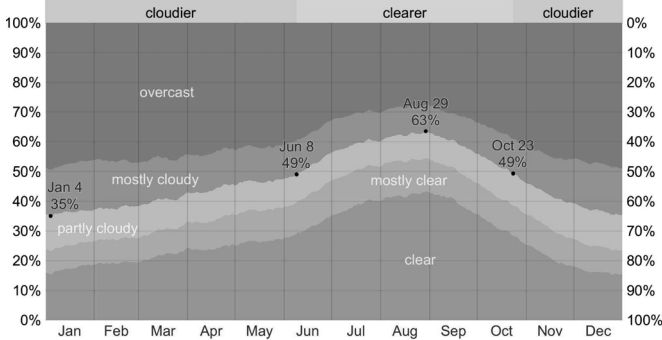


Figure 5: Percentage of time spent in each cloud cover band at Montreal. Source: [27].

annual saving of \$297 in 2019, increasing to \$381 in 2079. There is no significant difference between 13 kW and 26 kW batteries.

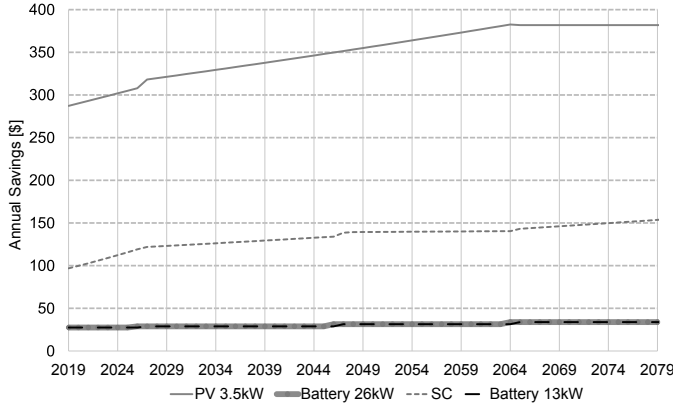
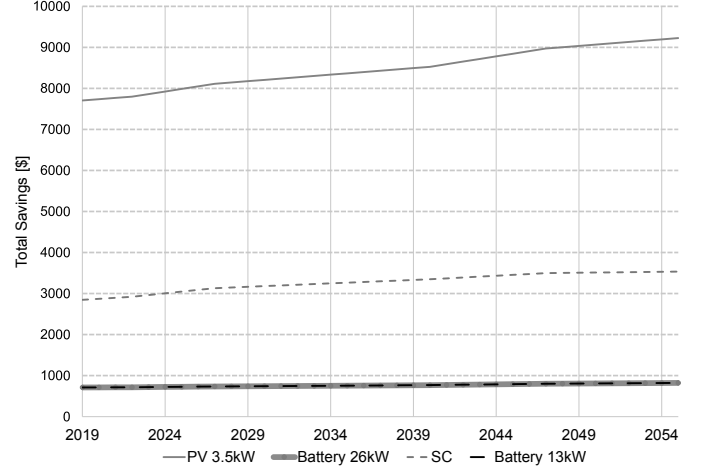
Figure 6: Annual saving (\$) for some $c \subseteq SHC^-$.

Figure 8 shows the payback for the 3.5 kW PV. In Figures 8 to 12 the x axis gives the start year for the project and the y axis gives the payback in years. The dashed red line indicates the life-span of 25 years. Three possible scenarios for inflation is considered. If it is 3% for 25 years after the installation year (2019), the expected payback is around 24 years. If it is 0.5% for 25 years after 2024, the payback is 25 years. If it is between 0.5% and 3%, the 3.5 kW PV will have a payback below its life-span between 2019 and 2024. An upper bound (UB) on the start of the project is 2024, since the system starts to be cost-effective for the most conservative value of inflation. A

Figure 7: Total savings (\$) from the year that project starts for some $c \subseteq SHC^-$.

lower bound (LB) is 2019 since the system is cost-effective for 3% inflation.

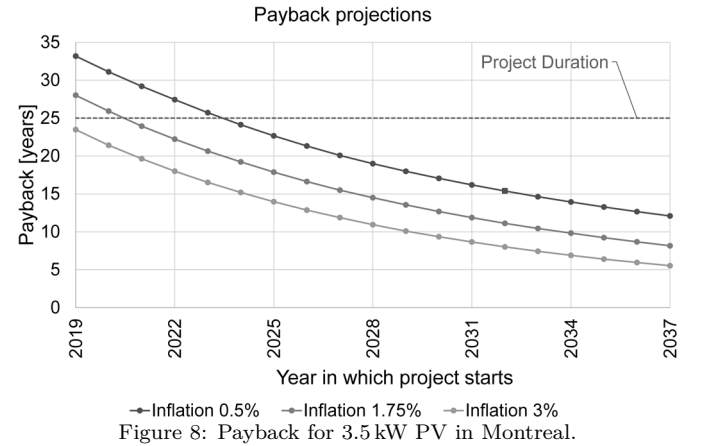
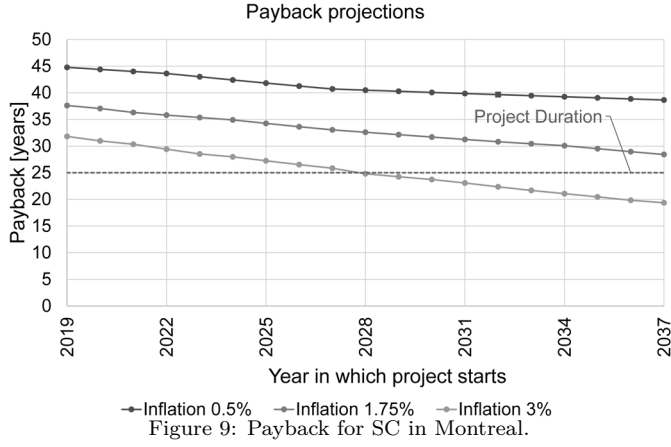


Figure 8: Payback for 3.5 kW PV in Montreal.

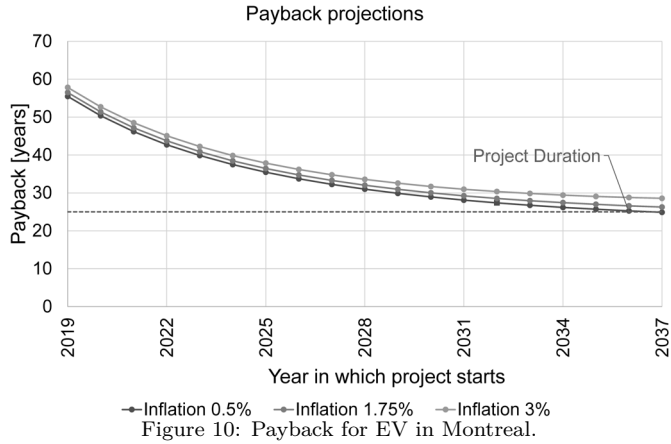
For a 6.5 kW PV system, the LB is 2019 and the UB is 2025. For 10 kW of PV, the LB is 2020 and the UB is 2025.

The SC system will not be profitable until 2028, as shown in Figure 9. With 1.75% inflation, the payback is 38 years if the project starts in 2019. A similar system had a payback above 75 years [69]. In this work, the heat-transfer fluid is a closed loop of water with self-draining. In [69], it is a glycol-based coolant with a circulation pump.

The system considered in this work is around three times less expensive than the glycol-based one, which explains the difference in the payback results.



Batteries are not used since there is a flat tariff so they are not cost-effective. EV is cost-effective after 2037: see Figure 10. The EV payback increases with the price of electricity. This is because the main source of savings is the replacement of fuel by electricity.



If the EV life-span is 10 years, the payback is positive after 2021; see Figure 11. If one includes the purchase rebate of \$8000 from the Drive Electric program of the Quebec government [70], the EV payback occurs between 2028 and 2031.

To summarize, in a scenario with higher inflation, the best option is to install a PV system in 2019–2020 and to use an EV after 2028 if the life-span is 5 years. Under conservative inflation, the best option is to install a PV system in 2024–2025 and to use an EV after 2031 if the life-span is 5 years. Batteries and SC should not be used.

4.4. Discussion

In this section, a comparison between the results of two previous examples is made and the framework generalization is discussed.

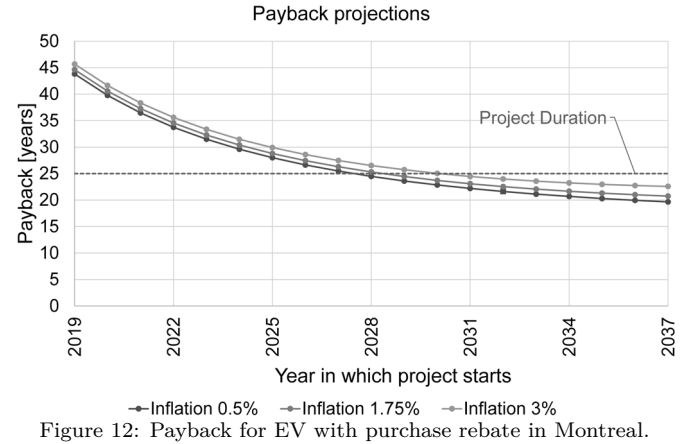
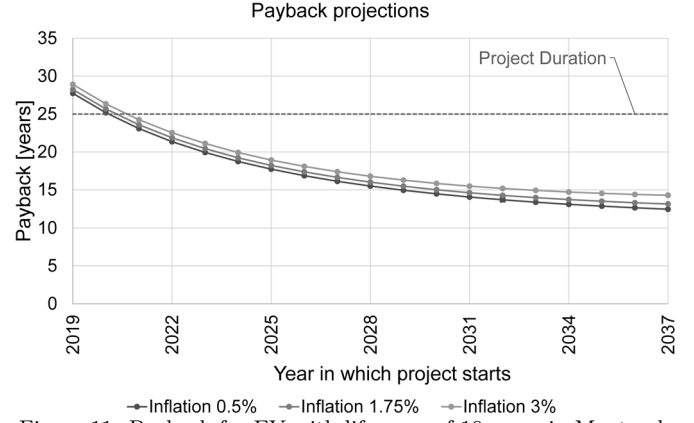


Table 6 shows the positive payback (+) and the negative payback (-) of some SHCs for the Belo Horizonte user and the London user. For PVs, the better capacity in terms of payback is highlighted. While the EV can be interesting for the London project, it is not of interest for the Belo Horizonte project. On the other hand, the SC can be worthwhile for the Belo Horizonte project, but not for the London project. This shows the dependence of the payback on the location and on the application of each given project.

Table 6 shows also a possible use of the framework for the determination of an approximate SHC size. For the London project, the PV should have a capacity between 3.5kW and 10kW. The framework could be run again replacing PV 3.5kW and PV 10kW by, for instance, PV 5kW and PV 8.5kW, respectively. This can help determine the good size for PV for the London project. For Belo Horizonte, the best PV capacity is estimated to be at least 10kW. If the user have yet space for extra panels, the framework could be run using higher PV capacities to determine if better results can be obtained.

The framework presented in this work is applicable to any location worldwide so long as the necessary input data for the framework can be acquired, so it is general. However, it does not mean that a user living in Belo Horizonte should directly use the results of the previous examples.

Table 6: Payback for different projects and cities.

SHC	London	Belo Horizonte
EV	+	-
SC	-	+
PV 3.5kW capacity	+	+
PV 6.5kW capacity	Better	+
PV 10kW capacity	+	Better

As stated before, the profitability of a project depends not only on the site but also on the application. For two householders in the same city, the inputs can be different and so will be the results of the framework. A simple example is a householder that lives in a house surrounded by buildings and another whose house has no nearby neighbours. The solar insolation will likely differ between them and this difference can significantly affect the profitability of PVs. As for any optimization model, a user must operate the framework using one's own data; in the case of this paper: data from its house structure, its consumption, the prices from its utility company, the local weather, etc.

A real application of the framework requires representative data for a given householder h . There are at least two ways to obtain this data. The first one is to use data available for the nearest geographical locations for weather, consumption behavior, and so on. Such data can be obtained from third-parties such as handbooks, literature, government reports, weather reports and databases, as was done for this work. However, these data may have low representation quality for some householders. The second option is to use sensors for data collection on solar radiation, temperatures, the power consumption of each appliance, etc. Although the second option requires an extra initial investment, it would more accurately represent householder h , so framework results are likely to be more representative. Data collection is a key component of a smart home, so its daily scheduling would have higher quality input, and more accurate results would be expected.

5. Conclusions

Transforming a house into a smart home requires considerable investment. This work proposed a framework to guide the transition to smart homes given customized electricity usage. The framework gives a payback analysis of each SHC acquisition combination for a specific user. The framework was tested on examples in Belo Horizonte, London, and Montreal. For BH and London, this work considered 1024 systems based on 8760 optimized hours (1 year). For Montreal, this work considered 64 systems based on 534360 optimized hours (60 years). The results quantify the dependence of the payback period on the site and on the application. The results also demonstrate the possibility to use the framework for SHC sizing. Examples are given to illustrate the versatility of the proposed framework.

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